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Plant Growth Model Using Artificial Neural Networks

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ABSTRACT

The goal of Advanced Life Support Systems (ALSS) is to provide self-sufficiency in life support for productive research and exploration in space. Important in reaching this goal is the production of crop plants in one or more controlled environments for the purpose of providing life essential food, air, and water to a human crew. To do this reliably and efficiently, it is necessary to achieve control of the rates of various plant physiology processes.

To develop an efficient control system that will be able to manage, control, and optimize plant-based life support functions, system identification and modeling of plant growth behavior must first be accomplished. We have developed a plant growth (physiology) model using artificial neural networks. Neural networks are suitable for both steady-state and dynamic modeling and identification tasks, since they can be trained to approximate arbitrary nonlinear input-output mappings from a collection of input and output examples. In addition, they can be expanded to incorporate a large number of inputs and outputs as required, which makes it simple to model multivariable systems.

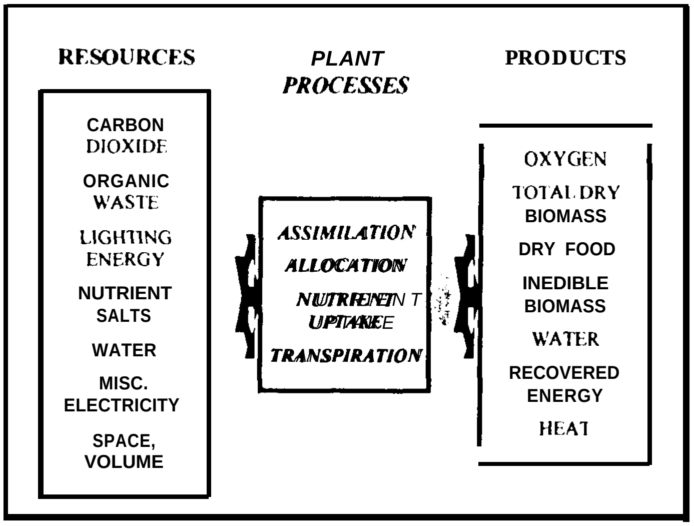
In this paper, we describe our motivation and approach to developing these models and the neural network architecture. Initial use of the artificial neural network for modeling the single plant process of transpiration is presented. The approach is to develop and validate neural network submodels describing the individual plant-based functions (assimilation, biomass allocation and accumulation, and resource demands) and to integrate them for full control of plant-based life support functions. With the use of neural networks, these complex, nonlinear, dynamic, multimodal, multivariable plant growth models will be able to better interpolate between various environmental conditions and parameters and be able to simulate responses and performance of various plants.

INTRODUCTION

One of the objectives for the Advanced Life Support Systems (ALSS) is to provide future spacecraft with advanced, integrated networks of micro-miniaturized sensors to accurately determine and control the physical, chemical, and biological environment for supporting human life for long duration missions.' To monitor all these networks of sensors, a "brain" or intelligent and autonomous control system needs to be developed with a high degree of reliability and robustness to establish and maintain in real-time life support and system functions. The control system must be able to collect multimodal sensor data in a continuous fashion for processing, data fusion, and integration, leading to timely generation of corrective control signals eliciting actuator function. To achieve safe and efficient support of crews during long-term space exploration or habitation, the system must be self-sufficient to a significant degree. The system must be optimized in providing air, water, and food, and processing and recycling of mass from waste products. Minimal involvement from crew members is required to allow them to perform their scientific and engineering tasks.'

Future regenerative life support systems providing a degree of self-sufficiency to crews will rely on plants to perform several functions. Plant remove CO_2 from the atmosphere and produce O_2 while incorporating carbon into biomass (food) through the process of photosynthesis or assimilation. Water is produced via the process of transpiration. Understanding the dynamic functions associated with assimilation, transpiration, biomass accumulation and allocation, as well as the demands for resources (resources recovered from wastes) is essential to designing and managing long-term operation of regenerative life support systems.

In pursuit of this objective, a control system is being developed and applied to managing, controlling, and optimizing plant-based life support functions. This will allow efficient growth of crop plants to provide the maximum amount of life essentials of air, water, and food to a human crew using the minimal amount of resources. It is necessary to achieve control of the rates of various plant physiology processes: assimilation, allocation, nutrient uptake, and transpiration. Figure 1 shows a block diagram mapping the resources and waste products into usable and recycled products using these four plant physiology processes.



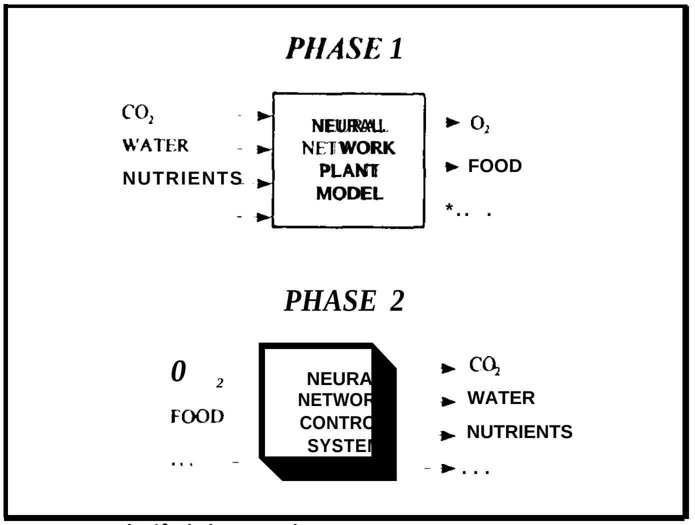
gure 1: Plant physiology processes converting resources to products for life support.

APPROACH

Since life support functions are dependent on plant performance, before developing a life support control system using artificial neural networks, the first step is the development of neural network models characterizing plant functions (Figure 2). These will provide a system identification and an understanding of plant behavior necessary for development of a life support system model. These models will also serve as tools to emulate and provide sufficient amounts of data over an adequately wider range of conditions and performance for training of the neural network control system.

While controlled environment crop production monitoring systems can generate huge amounts of data regarding environmental conditions and the maintenance of set-points, typical controlled environment production provides few data regarding the dynamics and control of the plant based life support functions. It is the response of plant-based life support functions over ranges of environmental conditions that enable prediction and lead to stable, autonomous control systems.

The neural network plant growth models will be developed and trained based upon a collation of various crop histories and mathematical computer models of plant growth. Using neural networks, all these individual models and crop data can be integrated to form a more complex, nonlinear, dynamic, multimodal model which will be able to better interpolate between various environmental conditions and be able to simulate short-term (day-to-day) and long-term (plant life cycle) growth of various plants.



igure 2: Artificial neural network model and control of plant growth.

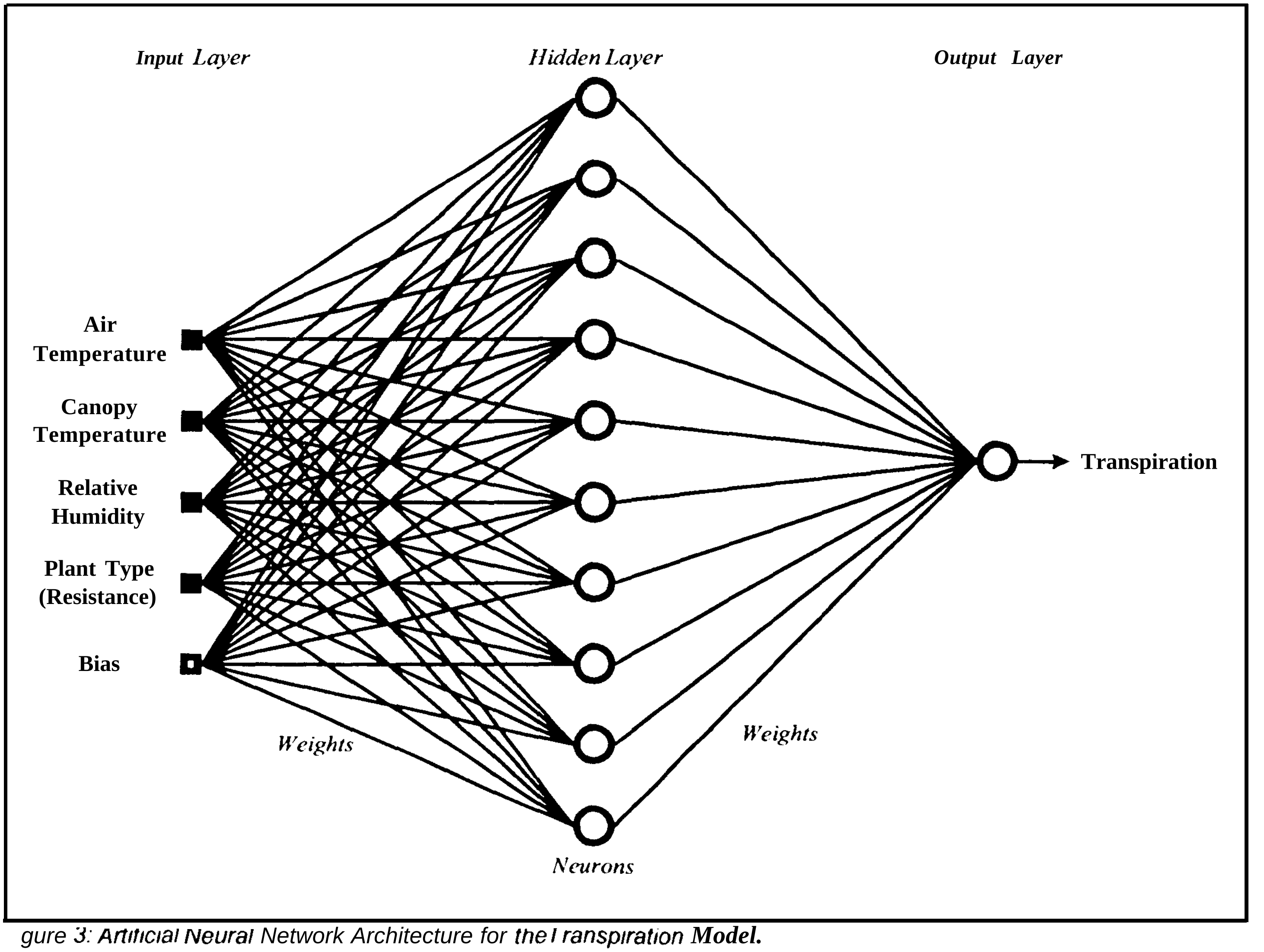
The second phase is the implementation of the artificial neural network control system for plant growth. With the plant growth models developed, the control system will be able to determine how to optimally grow the plants as required, specified, and/or determined by life support needs. For example, the control system will determine the minimum amount of energy (number of lights, photoperiod, nutrients, etc.) required to produce the necessary amount of oxygen and food for the crew members. This phase will lead to a real-time artificial neural network control system operating an actual plant growth chamber in managing, controlling, and optimizing plant-based life support functions.

ARTIFICIAL NEURAL NETWORKS

Inspired by biological systems, artificial neural networks are highly parallel data processing systems and are particularly suited to “learn” ill-defined or fuzzy input-output relationships and to perform adaptive interpolations.[2] Neural networks have been developed as generalizations of mathematical models of human cognition or neural biology. The structure of artificial neural networks are derived after the organization of the human nervous system, specifically the human brain.[3] They are composed of elements that perform in a manner that is analogous to the most elementary functions of the biological neuron. Although the resemblance is superficial, artificial neural networks exhibit such brain-like characteristics as their ability to learn from experience, generalize on their knowledge, perform abstraction, and make errors, which are all more characteristic of animal behavior than conventional digital computers.[2] The potential benefits of neural networks extend beyond the high computation rates provided by massive parallelism. They provide a greater degree of fault tolerance toward variations with input signals than digital sequential computers.[4] Neural network learning algorithms adapt their synaptic connection weights in time to improve performance based on the current results. Adaptation provides a degree of robustness by compensating for minor variations in the inputs as well as in the characteristics of the neurons. Traditional statistical techniques are not adaptive, typically processing all training data simultaneously before being given new data. Neural network classifiers are also non-parametric and make weaker assumptions concerning the shapes of underlying distributions than traditional statistical classifiers. They may thus prove to be more robust and realistic when distributions are generated by nonlinear processes and are strongly non-Gaussian.[4]

These neurally inspired architectures, with their capability to learn from experience rather than be cast in preset rules, have found widespread applications in a variety of fields including optimization, where an input pattern representing the initial values for a specific optimization problem is presented to the network, and the network produces a set of variables that represents a solution to the problem; and control, where an input pattern represents the current state of a controller and the desired response for the controller, and the output is the proper command sequence that will create the desired response.[2] They are already benefiting various applications that involve ill-defined transformations and prediction requirements ranging from health monitoring of internal combustion engines, gear boxes, and active suspension compensation for automobiles to real-time guidance and control of ballistic missiles in their target-acquisition, discrimination, and terminal homing phase.[5] Neural networks are capable of easily performing many tasks that conventional regression techniques and traditional artificial intelligence systems find difficult or impossible to solve.

A neural network is characterized by its pattern of connections between the neurons (architecture), its neuron function, and its method of determining the weights on the connections (training or learning algorithm). A variety of artificial neural network architectures and learning algorithms have been reported in the literature.[2,3,4] In general, the architecture can be defined as an interconnection (network) of



gure 3: Artificial Neural Network Architecture for the Transpiration Model.

neurons such that neuron outputs are connected, through synaptic weights, to other neurons including possibly themselves. The synaptic weights represent information being used by the network to solve a problem.

Two popular neural network architectures are the feedforward (Figure 3) and the feedback network structures. In the former, all external inputs are fed to a layer of neurons through synaptic weights in such a way that each input is fed to all of the neurons. Similarly each neuron in this layer is connected to each neuron of the next layer through synaptic weights. The layer may be similarly connected to another layer which may be the final layer giving the resulting outputs and thus called the output layer. The intermediate layers between the inputs and the output layer are termed hidden layers. This type of architecture is a feedforward network because of the forward flow of signals. A feedback network can be obtained from the feedforward network by connecting the outputs from the output layer to the input layer and using them as inputs. A special bias input is used as a weight on a connection from a unit whose activation is always "on" (or 1). The feedforward network can be used for optimization and modeling problems while the feedback network is generally used for controlling non-linear dynamical systems.[4]

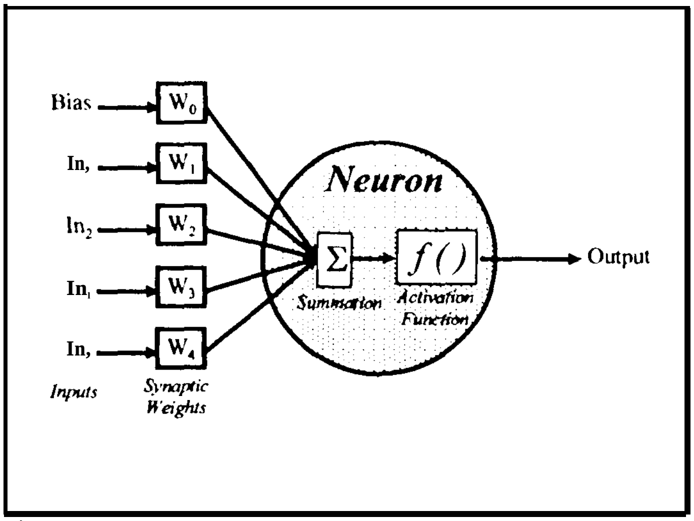
The neuron is a simple processing node with synaptic input connections and a single output. The basic operation of an artificial neuron involves summing its weighted input signals (representing synaptic strength) and applying a nonlinear output, or activation function (Figure 4). The summed value determines the activation level of the neuron. The bias weight represents a fixed threshold for the activation function. Different artificial neural network algorithms make use of different definitions of the activation function. Some examples are the hard-limiting activation functions (binary functions) called threshold logic units and the soft-limiting activation functions (continuous functions) called sigmoidal functions (S-shaped). The sigmoidal function is defined by:

$$f(x) = \frac{2}{1+\exp(-\lambda x)} - 1$$

for bipolar outputs (values in the range of -1 and 1) where λ is the gain of the neuron which is the steepness of the continuous function near x = O. The bipolar sigmoidal function can also be represented by the hyperbolic tangent function:

$$\tanh\left(\frac{x}{2}\right) = \frac{1-\exp(-x)}{1+\exp(-x)}$$

Figure 5 shows the bipolar sigmoidal function with the gain (λ) set to 1.



igure 4: *Neuron mode/.*

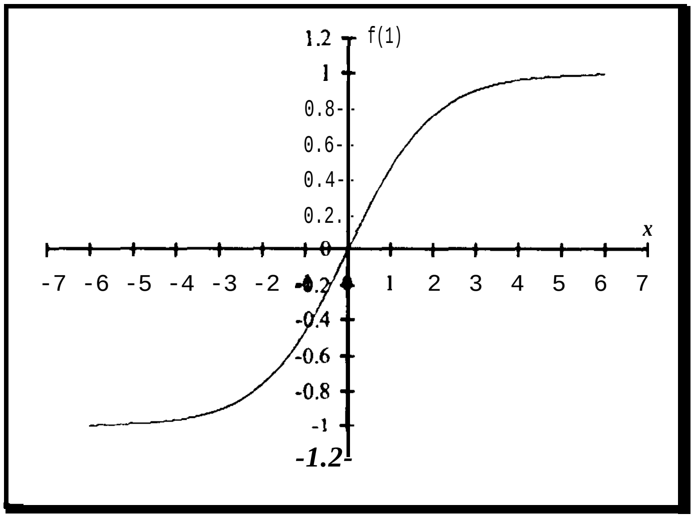


Figure 5: Bipolar sigmoidal function with?. =1.

The backpropagation (generalized delta rule) learning algorithm" is" one of the various methods available to train a neural network architecture. It is a gradient descent method to minimize the total squared error of the output computed by the network. The training of the network by backpropagation involves three stages: the feedforward of the input training pattern, the calculation and backpropagation of the associated error, and the adjustment of the weights. During feedforward, each input signal is sent to each of the hidden neurons. Each hidden neuron then computes its activation and sends its signal to each of the output units. Each output unit computes its activation to form the responses of the network for the given inputs. During training, the output units compare their computed results with their target values to determine the associated error for the given inputs. Based on this error, an error factor is computed which is used to distribute the error at the output neurons back to all the neurons in the hidden layer. This factor is also used to update the weights between the output and the hidden layer. In a similar manner, an error factor is computed for each of the hidden neurons and is used to update the weights between the hidden layer and the input layer. The weights for all layers are then adjusted simultaneously. This process is iterated numerous times until the network converges on the solution of the problem and the associated error at the output is minimized. After training, application of the network involves only the computations of the feedforward phase.

PLANT GROWTH MODELS

Four crop processes have been identified as critical to crop-base life support systems operation.[6] Taken together these processes result in a complete life support system package which can be highly reliable and controllable.

ASSIMILATION - This is the process by which crop plants convert carbon dioxide to plant biomass. Oxygen is released in the process. A crew member generates about one kilogram of carbon dioxide per day which can be converted through crop assimilation. Modeling and controlling this process will facilitate the design of crop-based systems for both air management and food production. The process is driven by the application of photosynthetic photon flux in the presence of carbon dioxide and appropriate temperature and nutrition.

ALLOCATION - Allocation is the process by which crop biomass is converted to edible plant components, whether they be green leaves and stems, seeds, flowers, roots, or tubers. The ratio of the edible biomass produced to the total biomass generated by assimilation is known as the harvest index. Another important aspect of allocation is the production of nutritional requirements of the crew, e.g. specific amino acids. In order to minimize the volume and power required to produce the food supply for each person in an isolated environment it is essential to maximize the harvest index. The allocation process is driven by the rate of assimilation and is modulated by environmental factors which affect morphological development. These include crop canopy temperature, photoperiod, thermoperiod, and nutrition.

UPTAKE - As crop plants grow they require inorganic nutrient ions in order to build the chemical compounds which are important in plant growth and in human nutrition. The uptake of these ions is an active process which is driven by the requirements of assimilation and allocation. Failure of uptake of a critical element can result in poor crop performance and physiological damage such as tipburn in lettuce or blossom end rot in tomatoes. Excessive uptake can result in poor fruit development, low harvest index or toxicity symptoms. The control of uptake lies mainly with factors of the root zone such as nutrient solution oxygen concentration, pH, temperature, and specific ion concentrations.

TRANSPIRATION - This is the water production process of crop plants. More details are described in the next section which presents the mathematical models for this process.

TRANSPIRATION MODELS

The transpiration process is being modeled first, There are four different mathematical models for transpiration during crop growth: flow model using Ohm's law, transport flow model, radiation balance, and mass flux, These are discussed in more detail below.

FLOW MODEL (OHM'S LAW) - The simplest of the transpiration models to apply in crop production systems, the flow model is based on the familiar electrical model known as Ohm's law. Ohm's law states that flow (electrical current in Amperes) is equal to the potential difference (voltage) divided by the resistance to flow (measured in Ohms). The same basic model can be applied to transpiration from crop canopies. The flow of water molecules (kg S-l) into the air is a function of the water pressure difference (kg m^{-1} S^{-2}) between the leaf tissues and the air above. The resistance (s m^{-1}) in this case is the combined resistance of the leaf tissues, stomatal opening, and the boundary layer of the air adjacent to the crop canopy.

$$\text{Transpiration} = \frac{\text{vapor pressure difference}}{\text{resistance to flow}}$$

$$= \frac{Æe}{r_c}$$

where:

Æe = (Saturation vapor pressure of crop canopy tissues) - (Vapor pressure of atmosphere)

r_c = Total functional resistance of tissues and atmospheric boundary layer to flow

Calculation of transpiration through use of this model requires measurement of air temperature, relative humidity, and mean crop canopy temperature. The saturation vapor pressures of the atmosphere and the crop canopy are calculated from the measured temperatures. The atmospheric vapor pressure is subsequently calculated from the saturation vapor pressure and relative humidity.

The most difficult of the variables to calculate is the canopy resistance r_c. In controlled environment crop production systems this value is often determined empirically and thereafter assumed to be constant for a specific crop in a specific production system. When air flow rates, crop size, energy flux, and crop water and nutritional status are consistently maintained this is a valid practice. The effect of stomata on the canopy resistance is considered to be minimal in most controlled cropping systems.'

FLOW MODEL (TRANSPORT) - This flow model is similar to the Ohm's law model in that the driving force for transpiration is assumed to be the difference in water content between the leaf tissue and the ambient air above it. However this model uses a gradient of specific humidity (measured in grams of water per kilogram of moist air). This value is readily calculated from atmospheric vapor pressure and total pressure and is very similar to the gradient of vapor pressure calculated above. Addition of the values for air density and latent heat of vaporization, calculated from measured parameters, provide a bit more opportunity to tune the estimate of transpiration.

The remaining parameter in the flow model is the transfer coefficient, an estimate of the capacity of the air to transport water away from the plant tissues. Monteith[8] discusses the estimation of this number from air flow, turbulence, shape, and roughness parameters.

$$\text{Transpiration} = (-\lambda_{va})(\rho_a)(K_W \frac{\delta q}{\delta z})$$

where:

λ_{va} = Latent heat of vaporization (kJ gi^{n}l)

ρ_a = Density of moist air (gm m^{-3})

$\frac{\delta q}{\delta z}$ = Gradient of specific humidity (m-')

K_W = Transfer coefficient- for water vapor in the atmosphere (m' S-l)

RADIATION BALANCE (BOWEN RATIO) - The radiation balance method of modeling transpiration relies on two calculated quantities: the net radiation (radiant energy) absorbed by a crop canopy, and the relative allocation of that energy between two heat transfer processes -- sensible heat transfer and latent heat transfer. The first of these requires measurement of net radiation in all wavelengths (W m^{-2}) absorbed by the crop canopy. This is readily accomplished using an instrument called a net radiometer.

The energy absorbed by a crop must be dissipated or the crop will heat up to unacceptable levels and tissues will die. The leaves of crops eliminate heat through the processes of transpiration and convective heat transfer. As has been shown above, transpiration is driven by the gradient of water vapor concentration from leaf tissues to the ambient air, where the vapor pressure of the leaf tissues is calculated as the saturation vapor pressure at mean canopy temperature. Sensible heat transfer is also driven by the temperature difference between the leaf tissues and the air above. As absorbed energy increases, the canopy temperature is driven up and both heat transfer processes increase. The relative rates of heat transfer by each process depend only on the mean crop canopy temperature and the atmospheric temperature and vapor pressure. A function called the Bowen Ratio is calculated from these two gradients and is applied to determine what percentage of the energy absorbed will be transferred through each process. An important assumption of this calculation is that the transfer coefficients for water vapor and sensible heat are equal. Merva[9] presents a mathematical development of this concept.

Net Radiation = Short-wave radiation + Long-wave radiation

$$R_N = R_S - r R_S + R_L - \sigma T^4 \ (\text{W } m^{-2})$$

where:

σ = Stefan - Boltzmann constant (5.6697E-8) (W m^{-2} K')

Transpiration = (Net Radiation) - (Sensible Heat Transfer) - (Temperature Change of Surface)

$$\lambda E = R_N - H - G$$

Assume temperature of surface at equilibrium = O.

$$\text{Bowen ratio } \beta = \frac{(c,)\ (ÆT)}{(\lambda)\ (Æq)}$$

where:

c_p = Specific heat of air

λ = Latent heat of vaporization

/ET = Temperature gradient from canopy to air

Æq = Specific humidity gradient from canopy to air

$$\text{Transpiration} = -\frac{R_N}{\lambda(\beta - 1)}$$

MASS FLUX - An estimation of transpiration can be made in many closed growth chambers by measuring the mass flow of water vapor into and out of the growing area of the chamber. Chambers in which this is possible have the closed cropping volume which is separated from the air conditioning system by ductwork. Calculations require measurement of the absolute humidity (g m^{-3}) of the air flowing into and out of the cropping area and is best done with dewpoint psychrometer. Also required is a measure of the mass flux of air into and out of the growing area through ducts, The transpiration rate is then calculated as the difference between the mass of water flowing into the chamber and that flowing out.

Transpiration = (Mass flow of water vapor into chamber) - (Mass flow of water vapor out of chamber)

$$= (\chi_{out} - \chi_{in})\, M$$

where:

χ = Absolute humidity (gm m^{-3})

M = Mass flow rate (m^3 S-l)

NEURAL NETWORK TRANSPIRATION MODEL

Since plant growth usually requires several weeks to several months to grow and neural networks require large amounts of training data, these mathematical models are used initially. These models provide the neural network with the necessary amount of training data and a wider range of input parameters. This training establishes a framework and a baseline for the neural network modeling. Experimental plant growth data is then used to fine-tune the neural network model. In this way, the plant growth experiments do not have to cover all the various input parameter combinations in order to train the network but only a few, particular endpoints, are needed to adjust and verify the neural network model performance.

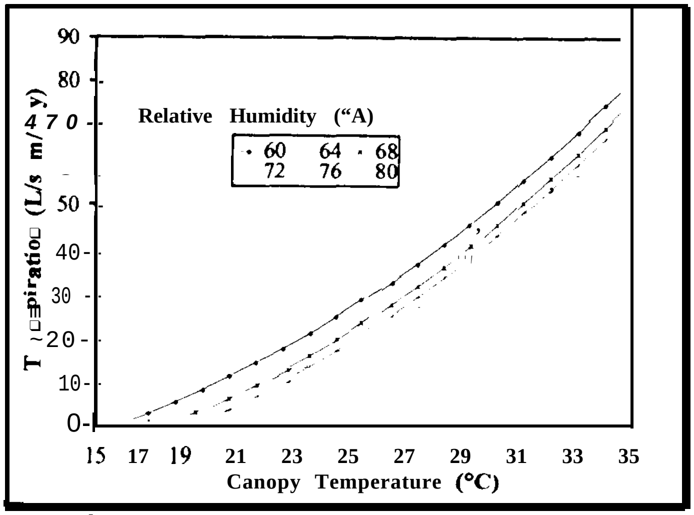
The neural network transpiration model is based upon the four mathematical models, particularly the Ohm's law flow model. The artificial neural network architecture (Figure 3) was developed to compute the transpiration rate given sensor readings of the air temperature, canopy temperature, relative humidity, and a resistance value identifying the type of plant. This resistance value is used as an input to allow this model the flexibility to accommodate for various plants. The operational range of the inputs for the transpiration model is given in Table 1. The network architecture used to model transpiration is a feedforward structure consisting of an input layer with 4 external inputs and a bias, a hidden layer with 10 neurons, and an output layer containing one neuron which produces the transpiration rate. Each neuron in the hidden and output processes its inputs as shown in Figure *4* and uses a bipolar sigmoidal function with a gain or ?. of 1 as shown in Figure 5. The neural network architecture is trained using the backpropagation learning algorithm.

Table 1: Transpiration Model Input Ranges.

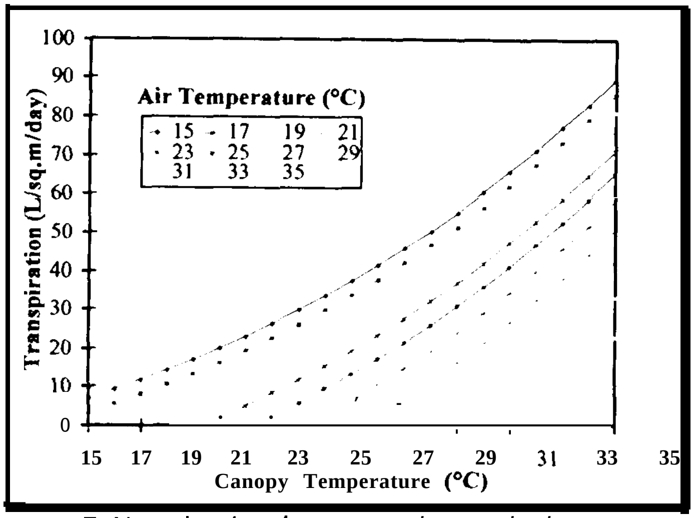
Sensor Measurements	Minimum	Maximum
Air Temperature	15 °C	35 'c
Canopy Temperature	15 °C	35 °C
Relative Humidity	60 9"	80 %
Resistance Value	**0.2**	**0.5**

Since the neurons use a bipolar sigmoidal function, the external inputs to the network need to be a value between the range of -1 and 1. Thus, each sensor measurement is scaled to this input range. For example, the relative humidity value is scaled such that 60% humidity is represented by -1 and 80% humidity is represented by 1, since these are the minimum and maximum workable values. Similarly, the output neuron produces a value in between this range and must be scaled appropriately to the transpiration rate in Liters/mete$/day.

The neural network was trained with the mathematical transpiration model for 9,960 iterations until the total squared error of the output of the network was less than 0.05. With this training, the artificial neural network has learned to approximate the mathematical transpiration model very accurately. Figure 6, 7, and 8



igure 6: Neural network generated transpiration rate for varying canopy temperature **and** relative *humidity with air temperature at 24 °C and resistance* **value** *at 0.3.*



gure 7: Neural *network generated transpiration rate for varying canopy and air temperatures with relative* humidify at 80 % *and plant type* of 0.3.

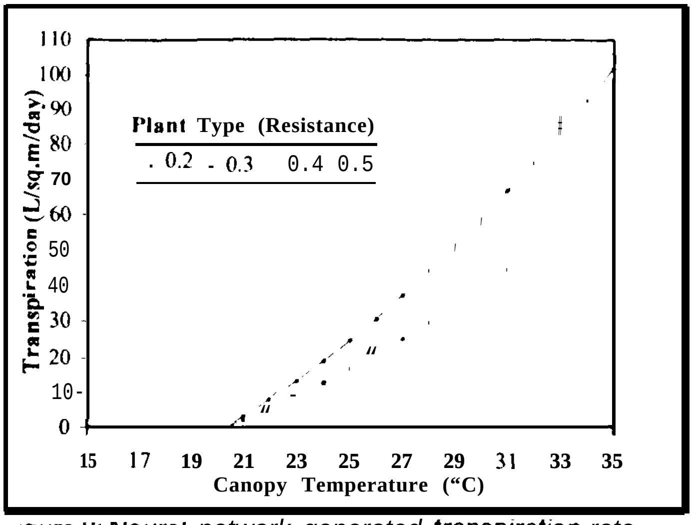


Figure 8: *Neural network generated transpiration rate for varying canopy temperature and different resistance values representing different plants with relative humidity at 80 % and air temperature at 24 'C.*

show the performance of the neural network transpiration model. In Figure 6, the transpiration rate is shown versus canopy temperatures with varying relative humidity for air temperature at a constant 24 'C and a resistance value (plant type) of 0.3. Both the canopy and air temperatures are varied with the relative humidity held constant at 80 % and a plant type of 0.3 in Figure 7. The neural network computed transpiration rates for different plant types are shown in Figure 8 with varying canopy temperature. This shows that the neural network transpiration model can be generalized to accommodate various species and types of plants by changing an input parameter.

CONCLUSION

To develop an intelligent, autonomous, and efficient control system that will be able to manage, control, and optimize plant-based life support functions, system identification and modeling of plant growth behavior must first be done. Artificial neural networks with their ability to learn and approximate arbitrary nonlinear input-output relationships from a collection of examples are very suitable for both steady-state and dynamic modeling and identification tasks. By integrating data from various mathematical plant growth (physiology) models and crop histories, neural networks can be trained to be complex, nonlinear, multimodal, multivariable plant growth models that will be able to better interpolate between various environmental conditions and parameters and be able to simulate growth of various plants.

One of major obstacles for the implementation of an artificial neural network model is the requirement for large amounts of training data over a range of environmental conditions. However, plant growth experiments usually require several weeks to several months, and typically very few data are recorded regarding life support plant functions and plant responses over this wide range of conditions. With the use of various mathematical models, the neural network can be initially trained such that a framework or a baseline for a plant growth process is established over this large range of environmental conditions, Then, the neural network can be fine-tuned with the limited real experimental data. This method will alleviate the need for numerous time-consuming plant growth experiments to cover all the various input parameter combinations in order to train the network and only a few, particular endpoints, will be needed to adjust and verify the neural network model performance.

Modeling of plant physiology processes can be divided to four submodels which are of significance and interest to ALSS: assimilation, allocation, nutrient update, and transpiration. A neural network architecture has been developed to model transpiration (water production) with varying inputs of air and canopy temperature, relative humidity, and plant type.

Artificial neural networks may be ideally suited as an intelligent computational methodology that would assimilate a variety of inputs from a sensor-suite in health monitoring of the ALSS and provide autonomous control of the environment. Furthermore, fully parallel, very large scale integrated (VLSI) hardware implementations of the customized neural network architectures for high speed, low power operations would be ideally suited for space deployment.

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